# Uncertainty, Social Valuation, and Climate Change Policy

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# Research question

*What are the socially optimally abatement and innovation policies in response to climate change under uncertainty?*

**What are the challenges?**

- multiple externalities (climate, innovation), policy levers (abatement, R&D), and sources of uncertainty (geosciences, economics).

**How do we address these issues?**

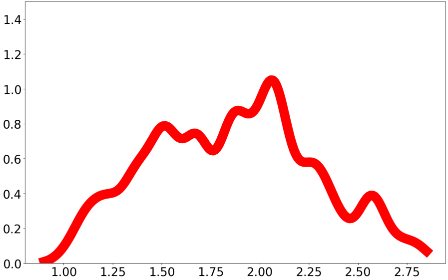
- General equilibrium framework applying dynamic decision theory to evaluate the impact of uncertainty on climate policy valuations.

**What do we find in our analysis?**

- Optimal policy emphasizes R&D, *substantial uncertainty impact* (non-monotonic); cautious emissions, *less uncertainty sensitivity*.

# Uncertain climate dynamics

We use **pulse experiment results** of Joos et al. (2013) and Geoffroy et al. (2013) to build a **set of climate sensitivity models** $\{\theta(\mathbf{m})\}_{\mathbf{m}=1,\ldots,\mathbf{M}}$:



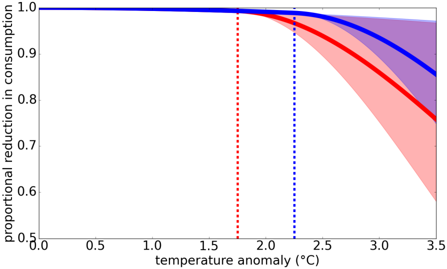

Smoothed density for the exponentially weighted (over horizon) responses of temperature to an emissions pulse based on input from 144 different models denoted by $\theta(m)$ for $m = 1, 2, \ldots, 144$.

**Stochastic model of climate dynamics**: $dY_t = \mathcal{E}_t(\theta(m)dt + \varsigma dW_t)$

- Matthews et al. (2009) linearity (and permanence) with Palmer and Stevens (2019) stochastics

# A stochastic model of damages

**Log-Quad Damages:** $d \log N / d\hat{y} = \underbrace{\lambda_1 + \lambda_2 y}_{\text{baseline}} \underbrace{+ \lambda_2 (\bar{y} - \hat{y}) + \lambda_3(\ell)(y - \hat{y})}_{\text{post-jump realization}}$




Range of possible damage functions for jump threshold of $Y_t = 1.75$ (red) and $Y_t = 2.25$ (blue).

- Uncertainty comes from a jump process with $L - 1$ absorbing states.
- Each state corresponds to a $\lambda_3(\ell)$ with prior probability $\pi^d(\ell)$.
- Jump intensity localized to $[\underline{y}, \overline{y}]$, with $\tilde{y}$ where the jump occurs.

**Novel *information dynamics* about uncertain future climate damages.**

# Preferences, production, and emissions

The planner has **recursive preferences over damaged consumption**:

$$\left(\frac{\delta}{1-\rho}\right)\left[\left(\frac{\widetilde{C}_t}{V_t}\right)^{1-\rho}-1\right], \quad \widetilde{C}_t = C_t/N_t$$

- $1/\rho$ is the intertemporal elasticity of substitution (IES).

Output is generated using **AK production technology** where:

$$d\log K_t = \left[\mu_k + \left(\frac{I_t^k}{K_t}\right) - \frac{\kappa}{2}\left(\frac{I_t^k}{K_t}\right)^2\right]dt - \frac{|\sigma_k|^2}{2}dt + \sigma_k dW_t^k.$$

- $K_t$ is broadly conceived (e.g., physical, human, & intangible capital).

Utility negatively impacted by **economic damages from climate change**

- Production generates emissions, increasing climate change and $N_t$.

# Carbon abatement technology and innovation

We consider the following **carbon abatement technology**:

$$\alpha K_t \left[1 - \phi_{0,t}(B_t)^{\phi_1}\right] = C_t + I_t^k + I_t^r, \qquad B_t = \left(1 - \frac{\mathcal{E}_t}{\beta\alpha K_t}\right)\mathbb{I}_{\{\mathcal{E}_t < \beta\alpha K_t\}}$$

**Innovation** reduces $\phi_{0,t}$, arrival rate based on **knowledge stock** $R_t$:

$$dR_t \quad = \quad -\zeta R_t dt + \psi_0 (I_t^r)^{\psi_1} (R_t)^{1-\psi_1} dt + R_t \sigma_r \cdot dW_t^R$$

- R&D ($I_t^r$) increases technology jump arrival rate $\mathcal{J}^L(R_t) = \chi R_t$

We model the shift to **carbon-neutrality** as a one-state jump process:

- Pre Jump: $\phi_{0,t} = \bar{\phi}_0$; Post Jump: $\phi_{0,t} = 0$

# Framework for uncertainty

**Now we introduce jump and diffusion model misspecification**:

- Hansen and Sargent (2001, 2011); Maccheroni et al. (2006)

**Optimize social welfare, constrained uncertainty consequences**:

$$V(\boldsymbol{x};\alpha) = \max_{\boldsymbol{\alpha}} \min_{g,h} \mathbb{E}\left[\int \exp(-\delta t)\left(U(C;\boldsymbol{x},\alpha) + RE(g,h)\right) dt\right]$$

$$RE(g,h) = \xi \sum_{\ell=1}^{L} \mathcal{J}^{\ell}(x)\left[1 - g^{\ell}(\boldsymbol{x}) + g^{\ell}(\boldsymbol{x}) \log g^{\ell}(\boldsymbol{x})\right] + \xi \frac{1}{2} h(\boldsymbol{x})' h(\boldsymbol{x})$$

- Two-player, zero-sum differential game w/ relative entropy constraint

**Introduces endogenous, state-dependent drift and jump distortions**

$$g^{\ell,\star}(\boldsymbol{x}) = \exp\left(-\frac{1}{\xi}\left[V^{\ell}(\boldsymbol{x}) - V(\boldsymbol{x})\right]\right) \quad h^{\star}(\boldsymbol{x}) = -\frac{1}{\xi}\sigma_x(\boldsymbol{x})'\left(\frac{\partial V}{\partial \boldsymbol{x}}(\boldsymbol{x})\right)$$

- (Probabilistic) characterization of misspecification concerns

# Valuation adjustment for uncertainty

We examine **altered probabilities** implied by the following:

- *misspecifying* the damage distribution & damage arrival
- *misspecifying* the technological innovation arrival
- *misspecifying* the climate sensitivity model
- *misspecifying* the economic productivity

From a decision theoretic perspective, $\xi$ is a **"preference parameter"** that governs aversion to uncertainty broadly conceived.

The constructed **"worst-case" probabilities** from two-player game act as **uncertainty adjustments** in the SP's valuation formulations

The **altered probabilities** are not intended to be the beliefs of the planner, but rather they **reflect the magnitude of their uncertainty concerns**.

# Quantitative storytelling via social valuations

**Social valuations (SV) serve as "asset prices" characterizing the economic externalities induced by climate change and innovation.**

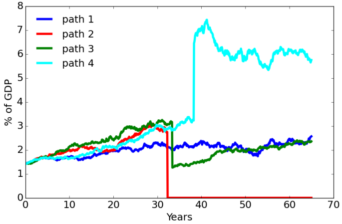
- "social cash flow": impulse response from an increase in emissions or R&D to an impact on future state variable outcomes (marginal).
- This "cash flow" is discounted stochastically in ways that account for a broader (quantifiable) perspective on uncertainty.

**Show distorted probabilities, optimal actions (closely tied to SVs)**:

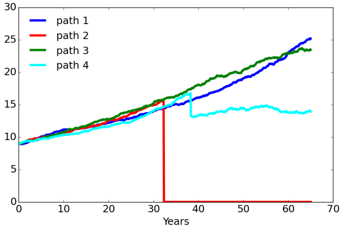
- $\bar{\theta}$ avg. of 144 climate models, 20 damage models $\lambda_3 \in \{0, \ldots, 1/3\}$
- Misspecified jump processes, climate-economic model dynamics
- $\xi = \infty$ (neutrality), $\xi = 0.1$ (less), $\xi = 0.05$ (more)
- $\phi_0 = 0.5$, $\rho = 1$, $\delta = 0.01$, remaining set to match data and literature

**Simulated zero-shock trajectories under baseline probabilities.**

# Stochastic Pathways



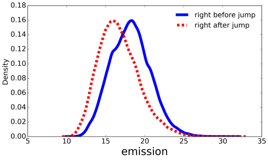

(a) R&D investment



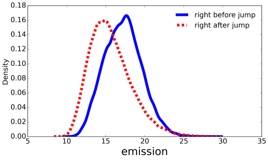

(b) emissions

- (P1) no jump; (P2): tech jump; (P3) good dmg; (P4) bad dmg
- Strong R&D investment with shifts for damage realizations
- Increasing emissions tempered by tech., damage jump shifts

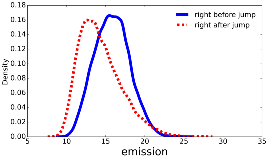
# Emissions before and after a damage realization event




(a) baseline




(b) less aversion

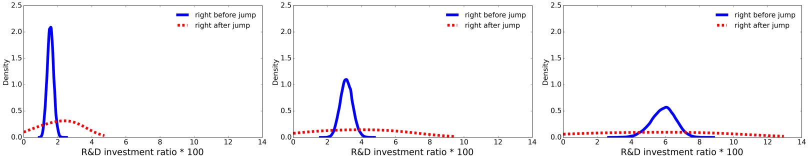



(c) more aversion

The blue line shows the distribution of outcomes just before a damage jump realization, and the red dashed line shows the distribution of outcomes just after a damage jump realization.

- “wait for more info”: emissions down after damage jump
- median response differences are between $10\% - 12\%$.
- modest emissions reduction (before) from increased aversion

# R&D investment before and after a damage realization event

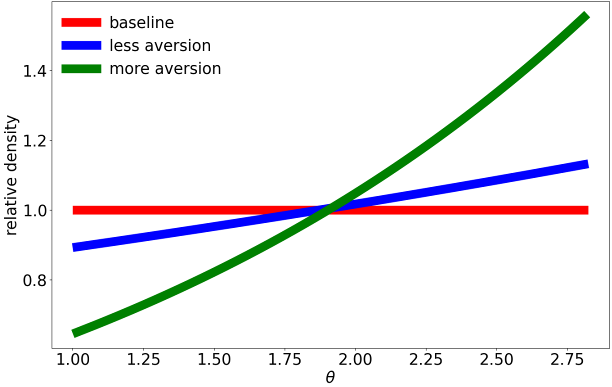



(a) baseline (b) less aversion (c) more aversion

The blue line shows the distribution of outcomes just before a damage jump realization, and the red dashed line shows the distribution of outcomes just after a damage jump realization.

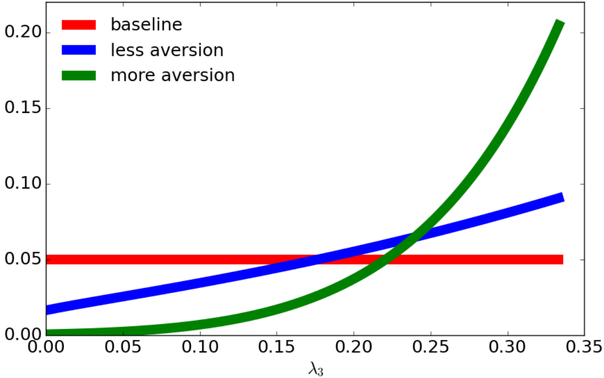
- R&D responses much more heterogeneous after damage jump
- spread (& median) increases when activating robustness concerns
- amplified sensitivity to uncertainty of R&D relative to emissions

# Climate uncertainty plot



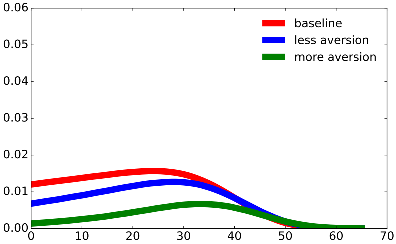

Uncertainty-adjusted densities for temperature responses to cumulative emissions. The baseline and two uncertainty-adjusted densities are relative to a uniform baseline density.

# Damage curvature densities

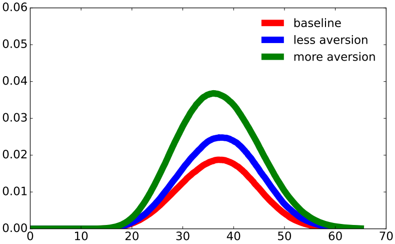



Uncertainty-adjusted probabilities for the alternative damage curvatures.

# Jump time density




(a) Contribution of technology jump.




(b) Contribution of damage jumps.

Jump-time densities under the baseline probability and uncertainty-adjusted probabilities for two specifications of uncertainty aversion.

- decreasing the likelihood and arrival of tech jump
- increasing likelihood first jump is damage type

# Uncertainty Decomposition

| | SVRD | | R&D / output | |
|---|---|---|---|---|
| **Uncertainty channel** | $\xi = .1$ | $\xi = .05$ | $\xi = .1$ | $\xi = .05$ |
| baseline | 66% | 43% | .0063 | .0063 |
| climate uncertainty | 66% | 44% | .0063 | .0064 |
| damage uncertainty | 68% | 46% | .0067 | .0071 |
| productivity uncertainty | 65% | 42% | .0061 | .0058 |
| technology uncertainty | 93% | 82% | .0123 | .0223 |
| all channels | 100% | 100% | .0144 | .0334 |

SVRD and R&D investment-output ratios when different uncertainty channels are activated.

- technology uncertainty is the dominant channel
- R&D investment amplified as aversion is enhanced
- SCGW decomposition similar, uncertainty sensitivity more modest

# SVRD and corresponding investments for alternative $\xi$

| $\xi$ | $\infty$ | .10 | .05 | .01 | .009 | .008 | .007 |
|---|---|---|---|---|---|---|---|
| SVRD | 3.43 | 4.87 | 6.67 | 6.69 | 6.15 | 5.57 | 4.91 |
| R&D inv. | .0075 | .0151 | .0283 | .0288 | .0243 | .0200 | .0155 |

Social value of R&D (technology jump only) as a function of the robustness penalty parameter, $\xi$. Larger values of $\xi$ imply smaller aversions to uncertainty.

# Why is there more proactive investment in R&D?

**Social Valuations provide an "asset pricing"-style interpretation:**

- social "discount": $\delta + \sum_{j=1}^{n} \mathcal{J}^j(X_u^j) g^j(X_u^j)$
- social "cash-flow": $\mathcal{J}^i(X_t^i), \frac{\partial \mathcal{J}^i}{\partial x_i}(X_t^i), g^i(X_t^i), V(X_t), V^i(X_t), \frac{\partial V^i}{\partial x}(X_t)$
- key for SVRD: longer-term "cash-flow" of uncertain jump processes

**Two countervailing forces of uncertainty for the SVRD:**

- more pessimistic about the R&D timing (delayed success).

$$\mathcal{J}^L(X_t) > g^L(X_t)\mathcal{J}^L(X_t)$$

- greater value to innovation due to reduced uncertainty exposure.

$$\left[\frac{\partial \mathcal{J}^L}{\partial x}(X_t)\right] g^L(X_t) \left[V^L(X_t) - V(X_t)\right]$$

Second force dominates in our computations over "interesting" range of $\xi$.

# Additional Insights and Considerations

**Key related features of the model to keep in mind**:

- this is “big project” R&D (Manhattan project or Apollo program)
- uncertainty is about the timing of a successful outcome
- R&D increases likelihood of innovation (unlike portfolio allocation)

**We explore alternative parameter settings in the paper**:

- alternative abatement ($\phi_0$), discount ($\delta$), and EIS ($\rho$) values explored
- values influential for quantitative, not qualitative, SV outcomes

**Uncertainty Aversion vs. Recursive Utility Interpretation**:

- mathematical equivalence under certain conditions ($\gamma = \frac{1}{\xi} + 1$)
- decomposition isolates specific channels, breaking equivalence
- clear scientific, economic justification for model uncertainty

**Omitting various policy frictions that could be relevant**:

- (Bloom et al., 2019; Hall and Sena, 2017; Acemoglu et al., 2012, 2016)

# Conclusions

**We provide a novel framework for characterizing the implications of climate-economic model uncertainty for social valuations**

- refines and extends methods from decision theory and asset pricing
- accounts for geophysical, technological, and economic uncertainty

**Our quantitative uncertainty assessment provides novel insights:**

- Technology the dominant uncertainty channel impacting social valuations, followed by climate damage uncertainty
- R&D investment a key tool for socially prudent policy, which is often substantially augmented by uncertainty concerns.
- Non-monotonic response of R&D investment to uncertainty aversion for “extreme” cases when innovation seemingly unattainable
- Emissions show immediate caution but less sensitive to uncertainty, pathways contrast gradual emissions reduction policies.

# Appendix

## Appendix

# References


- Hansen, L. P., & Souganidis, P. (2025). Stochastic responses and marginal valuation. *PNAS*.
- Barnett, M., Brock, W., Hansen, L. P., & Zhang, H. (2026). Uncertainty, social valuation, and climate change policy. *SSRN working paper*.

# Additional Key Citations - Economics and Finance

**Climate-Econ:** Golosov et al. (2014), Nordhaus (2018), Cai et al. (2017), Acemoglu et al. (2016), Van den Bremer and Van der Ploeg (2021)

**Climate dynamics:** Arrhenius (1896), Eby et al. (2009), Matthews et al. (2009), Geoffroy et al. (2013), Joos et al. (2013), Pierrehumbert (2014), Ricke and Caldeira (2014), MacDougall et al. (2017), Palmer and Stevens (2019), Ghil and Lucarini (2020)

**Damage functions:** Lenton et al. (2008), Weitzman (2012), Cai et al. (2015), Nordhaus (2018), Drijfhout et al. (2015), Allen et al. (2019), and Ritchie et al. (2021), Cai and Lontzek (2019), Lemoine and Traeger (2014), Rudik (2020)

**Climate uncertainty:** Olson et al. (2012), Cai et al. (2015), Hassler et al. (2018), Nordhaus (2018), Dietz and Venmans (2019), Barnett et al. (2020)

**Decision theory:** Anderson et al. (2003), Maccheroni et al. (2006), Hansen and Sargent (2007), Klibanoff et al. (2009), Hansen and Miao (2018), Barnett et al. (2020), Hansen and Sargent (2023), Hansen and Sargent (2022), Cerreia-Vioglio et al. (2025)

# Climate change consequences and uncertainty

*It is unequivocal that human influence has warmed the atmosphere, ocean and land. ... human-induced climate change, including more frequent and intense extreme events, has caused widespread adverse impacts and related losses and damages to nature and people, beyond natural climate variability.*

***– IPCC (2021); Pörtner et al. (2022)***

*The economic consequences of many of the complex risks associated with climate change cannot, however, currently be quantified... these unquantified, poorly understood and often deeply uncertain risks can and should be included in economic evaluations and decision-making processes.*

***– Rising et al. (2022)***

# Sources and types of uncertainty

**We embrace and confront uncertainty in a unified framework**

- incorporating alternatives model rather than discarding them
- identifying forms of uncertainty that are most consequential

**Exploring multiple types of model uncertainty**

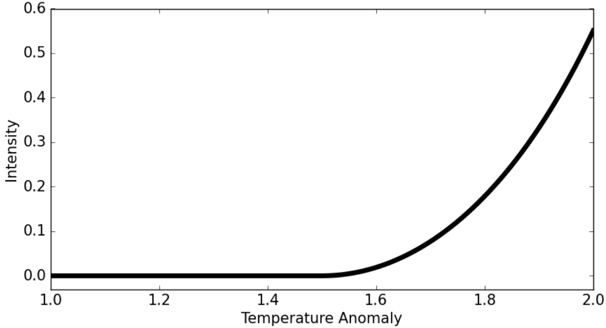
- risk (within models): unknown outcomes with known probabilities
- misspecification (about models): unknown probability model flaws

**Accounting for consequence of multiple uncertainty sources**:

- *carbon-climate dynamics* mapping emissions into temperature
- *economic damage functions* depicting climate-linked output losses
- *technological innovation* leading to a carbon neutral economy
- *economic productivity* related to growth of the capital stock

# Intensity function

**Damage arrival rate:** $\mathcal{J}^{\ell}(y) = \begin{cases} r_1 \left(\exp\left[\frac{r_2}{2}(y - \underline{y})^2\right] - 1\right) & y \geq \underline{y} \\ 0 & 0 \leq y < \underline{y} \end{cases}$




Intensity function, $r_1 = 1.5$ and $r_2 = 2.5$. With this intensity function, the probability of a jump at an anomaly of 1.6 is approximately .02 per annum, increasing to about .08 per annum at an anomaly of 1.7, increasing further to approximately .18 per annum at an anomaly of 1.8 and then to about one third per annum when the anomaly is 1.9.

# Social valuations

**Social valuations (SV) serve as our metric for characterizing the economic externalities induced by climate change and innovation.**

- allows us to quantify and assess the impact of model uncertainty

**In our uncertainty analysis, we depict the SVs as asset prices**

- "social cash flow": impulse response from an increase in emissions or R&D to an impact on future state variable outcomes (marginal).
- This "cash flow" is discounted stochastically in ways that account for a broader perspective on uncertainty.

We represent **uncertainty adjustments as changes in probability distributions** over future outcomes for the macroeconomy and climate.

**Social valuations and optimal actions closely tied via FOC**

# Computational challenges

**We solve for the planner's solution using sequential method:**

i) compute VF conditioned on both jumps happening;

ii) compute VFs for each realized damage curve allowing for a technology jump in the future and using step i) VF as input;

iii) compute VF for the realized technology jump allowing for a damage state jump in the future and using i) VFs as input;

iv) compute VF prior any jumps occurring taking the VFs from steps ii) and iii) as inputs.

We solve **coupled PDEs** where the solutions to **one set** of PDEs are **inputs** into **another PDE** of particular interest.